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Network Dependence in the Euro Area Money Market

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Abstract

I estimate network dependence effects in the euro area unsecured overnight interbank market during the financial crisis. I use linear spatial regressions to estimate the dependence of individual banks' trading volumes (and interest rates) on the trading volumes (and interest rates) of their network neighbours. Neighbours are defined from past trading relations. I find that banks' net lending volumes and lending-borrowing interest rate spread depend negatively on their neighbours' respective outcomes. By contrast, there arise positive effects for total trading volume and borrowing rates. Overall, however, these effects are small and significant only in periods of market turmoil or of major policy interventions. The results suggest that neighbours act as a buffer in absorbing idiosyncratic liquidity shocks.

JEL Codes: C21, E42
Keywords: Euro area money markets, financial crisis, network analysis, spatial regressions

Non-Technical Summary

The disruptions in overnight interbank lending that occurred at various stages of the financial crisis and of the euro area sovereign debt crisis have triggered a number of studies aimed at a better understanding of overnight interbank markets. One strand of research has analysed the network structure of interbank lending relationships, which arises from persistent trading relationships in interbank markets: many banks appear to entertain stable borrowing relationships with a small set of other banks. They borrow larger volumes and obtain more favourable interest rates from their relationship lenders.

Such stable bilateral lending relationships define an interbank network. Little is known however about the extent to which individual banks are indeed affected by these relationships, as e.g. by the impact of an idiosyncratic liquidity shock in their network neighbourhood.

The present paper studies this issue from a data set on *unsecured overnight interbank loans* among 322 banks located in the euro area in between January 2008 to March 2013. It applies linear spatial regression models to estimate network dependence effects in trading volumes and interest rates, that is, the degree to which the individual banks' lending and borrowing volumes and interest rates depend on the respective outcomes of their neighbours in the network.

I find predominantly negative network dependence in net lending volumes and the lending-borrowing interest rate spread, and predominantly positive effects for total volumes. However, effects remain generally small and are significant only in periods of market turbulences or of major ECB interventions. I do not find evidence for network dependence in lending or borrowing volumes and lending rates. The estimates do not support the view that network dependence would have played an important role in the propagation of shocks in the market during the financial crisis. The negative estimates for net lending volumes and the lending-borrowing spread suggest that neighbours acted as a buffer to partly absorb idiosyncratic liquidity shocks by counterbalancing their own net lending positions.

1 Introduction

A number of papers have studied the topology of interbank networks in the U.S. and in various national European markets. These studies document several salient features of interbank networks, such as scale-free degree distributions (e.g. Soramäki et al., 2006; Bech and Atalay, 2008), a pronounced core-periphery network structure (e.g. Craig and von Peter, 2014; Lelyveld and in't Veld, 2012), and the presence of persistent trading relationships (e.g. Cocco et al., 2009; Afonso et al., 2011; Bräuning and Fecht, 2012). Little is yet known about the implications of the network structure on the allocation of interbank loans and on the interest rates paid on those. Indeed, a trading network is significant in economic terms only to the extent to which it affects prices and the allocation of liquidity: in a Walrasian market, any network graph based on present or past realised bilateral trades would be entirely irrelevant for market allocations. Put it differently, a network is of economic significance only to the extent to which the outcomes of an individual bank would depend on the outcomes of its neighbours in the network.

In this paper, I apply spatial regression models to estimate network dependence effects in trading volumes and interest rates in the euro area interbank market. I use a data set on unsecured overnight interbank loans among 322 banks located in the euro area that has been extracted by Frutos et al. (2014) from the ECB TARGET 2 payments platform. The data range from January 2008 to March 2013.

I define network dependence as the degree to which an individual bank's outcome depends on the outcomes of its neighbours in the interbank network. The network structure is defined from *past* bilateral trades. Various papers have provided strong evidence for the presence of persistent trading relations in interbank markets. Afonso et al. (2013) conclude that most banks in the U.S. interbank market form stable relationships with at least one lending counter-party. Borrowers pay lower prices and borrow more from their relationship lenders. Affinito (2012) and Bräuning and Fecht (2012) find similar evidence on the presence of persistent trading relations for Germany and Italy, respectively. Cocco et al. (2009) and Bräuning and Fecht (2012) confirm that banks entertaining bilateral relationships agree on lower rates, although the latter study identifies such effect only for the period after the Lehman crisis.

Persistent bilateral relationships are however not a sufficient condition for the presence of network dependence effects. What matters is whether individual banks are potentially constrained by these relations, in the sense that an idiosyncratic liquidity shock in the neighbourhood of an individual bank would impact on the latter. Cohen-Cole et al. (2011) and Bräuning et al. (2015) present two theoretical models of the interbank market that give rise to such effects. Cohen-Cole et al. (2011) consider a strategic game, where an individual bank's profitability from lending activities would depend positively on the activities of its network neighbours. Increasing returns to scale give rise to strategic complementarity, which results in positive network dependence in both trading volumes and interest rates. Bräuning et al. (2015) present an extensive structural network formation model that features network dependence in interest rates due to costly peer-monitoring. In this model, a borrowing bank that faces scarce liquidity in its neighbourhood and is forced to resort to non-neighbours for obtaining a loan. It would then pay a higher interest rate on the latter, as establishing the new trading relationship is costly. This may also dampen trading volumes, but Bräuning et al. (2015) do not discuss such effects in their paper.

While spatial regressions have been applied to social and physical networks, to my knowledge, Cohen-Cole et al. (2011) is so far the only empirical study to estimate network dependence effects from linear spatial regressions in interbank markets.[1] Spatial regressions relate the outcome for a network node to the weighted average of outcomes of its neighbours, together with other explanatory variables. Cohen-Cole et al. (2011) consider intra-day snapshots of bilateral trades in the Italian overnight interbank market based on $1,000$ trades each. They report strong positive network dependence in lending volumes and rates. However, their econometric approach is subject to two shortcomings. First, they construct networks only from the subsets of banks that are active in a specific period and define neighbouring relations in a circular way from the actual trades within the same period. This might not only give rise to selection bias, but also violates the requirement of a predetermined weighting matrix in a spatial regression. Second, estimates do not allow for individual bank effects and thereby ignore that banks differ in their average trading volumes.

[1] See Lee et al. (2010) and Gibbons et al. (2014) for applications of spatial regressions to social networks.

I correct for these shortcomings by defining business relations from past transactions and allowing for fixed individual bank effects. The cost of this approach is that it requires aggregating the data over time and that it limits the analysis to banks that are active in a sufficient number of periods. I therefore aggregate the data to quarterly frequency and confine the analysis to banks that are active in almost all quarters. This leaves a set of 102 banks. I estimate the spatial regressions separately for each quarter using only cross-section information. In the period under consideration, network dependence may well vary over time given the disruptions in interbank markets during the financial crisis and the temporary fragmentation of European markets (Acharya and Merrouche, 2010; Angelini et al., 2011; Garcia-de-Andoain et al., 2014, 2015).

I find predominantly negative network dependence in net lending volumes and the lending-borrowing interest rate spread, and predominantly positive effects for total volumes and borrowing rates. However, effects are significant only in periods of either market turbulences or of major ECB interventions related to the euro area sovereign debt crisis. I do not find evidence for network dependence in lending or borrowing volumes and lending rates. These results are in sharp contrast to Cohen-Cole et al. (2011). The difference appears to be largely explained by the aforementioned caveats: when using their specification, I obtain results very similar to theirs.

My estimates do not support the view that network dependence would play an important role in the propagation of shocks in the market. Negative network dependence in net lending volumes and the lending-borrowing spread suggests that network relationships mitigate rather than amplify idiosyncratic shocks to the liquidity position of individual banks, as neighbours act as a buffer to partly absorb these shocks by counterbalancing their own net lending position.

The paper is organised as follows. After a review of spatial regression models in section 2, section 3 discusses various features of the euro area interbank market. Section 4 presents estimates from the spatial regressions. Section 5 concludes the paper.

2 The Linear Spatial Regression Model

Denote with $z_{ij,t} \geq 0$ the volume of lending from bank i to bank j in period t, with $i, j = 1, \ldots, n$, and $t = 1, \ldots, T$. Let $r_{ij,t}$ be the corresponding interest rate, which is defined if $z_{ij,t} > 0$.

Further, define with $z^L_{i,t} = \sum_{k=1}^n z_{ik,t}$ and $z^B_{i,t} = \sum_{k=1}^n z_{ki,t}$ the total lending and borrowing volumes of bank i, and with $z^V_{i,t} = z^L_{i,t} + z^B_{i,t}$ and $z^N_{i,t} = z^L_{i,t} - z^B_{i,t}$ its total trading and net lending volumes, respectively. The average lending rate of bank i is calculated as the volume-weighted average of bilateral rates $r^L_{i,t} = \left(\sum_{k=1}^n z_{ik,t} r_{ik,t}\right) / z^L_{i,t}$. With the average borrowing rate $r^B_{i,t}$ defined equivalently, denote with $r^N_{i,t} = r^L_{i,t} - r^B_{i,t}$ the lending-borrowing interest rate spread of bank i.

I analyse network dependence in trading volumes and interest rates using a linear spatial regression approach. I start from the spatial Durbin (SD) model (LeSage and Pace, 2009:28f),

$$y_t = \mu \mathbf{1} + \rho_0 W_t y_t + \rho_1 W_t y_{t-1} + \psi y_{t-1} + X_t \beta + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma). \tag{1}$$

The dependent variable $y_t = (y_{1t}, \ldots, y_{nt})'$ is an $n \times 1$ vector that may represent any of the aggregate variables defined above, i.e. trading volumes $\left\{z^L_{i,t}, z^B_{i,t}, z^V_{i,t}, z^N_{i,t}\right\}$ or interest rates $\left\{r^L_{i,t}, r^B_{i,t}, r^N_{i,t}\right\}$. The network structure is represented by $n \times n$ weighting matrix W_t, which is predetermined to y_t. The matrix is scaled such that its rows sum up to one. Its precise definition depends on the dependent variable and will be discussed below. X_t represents an $n \times k$ matrix of control variables, while μ is a scalar constant term, multiplied with $n \times 1$ vector $\mathbf{1} = (1, \ldots, 1)'$.

The basic research question of this paper is whether the outcomes for bank i, y_{it}, depend on the weighted averages of outcomes of its neighbours. The latter are given as the elements of $W_t y_t$ and $W_t y_{t-1}$, respectively. For instance, with y_{it} being the total trading volume of bank i, the i^{th} element of $W_t y_t$ represents the average contemporaneous total trading volume of the neighbours of bank i. The key coefficients of interest are ρ_0 and ρ_1, which describe the dynamic impact of the total trading volumes of the neighbours of bank i on the trading volume of bank i itself.

To ensure that weighting matrix W_t is predetermined to y_t, I define it from the bilateral trading volumes from the *previous* quarter. The precise definition of W_t depends on the dependent variable. For lending volumes, $z^L_{i,t}$, and rates, $r^L_{i,t}$, I set $W_t = (w^L_{ij,t})^n_{i,j=1}$ with weights given as

$w^L_{ij,t} = z_{ij,t-1} / z^L_{i,t-1}$. The case of borrowing ($z^B_{i,t}$ and $r^B_{i,t}$) is treated equivalently with weights $w^B_{ij,t} = z_{ji,t-1} / z^B_{i,t-1}$. For total, $z^V_{i,t}$, and net lending volumes, $z^N_{i,t}$, and the lending-borrowing spread, $r^N_{i,t}$, I use weights $w^V_{ij,t} = (z_{ij,t-1} + z_{ji,t-1}) / z^V_{i,t-1}$, which represent the undirected interbank network. The choice of a one-quarter window follows Bräuning and Fecht (2012). The results presented in section 4 are stable with respect to using longer moving average windows.

I turn to estimation and identifiability issues. By simple re-arrangement, equation (1) can be recast to separate level ($\overline{\rho}$) from change (ρ_0) effects in spatial correlation

$$\Delta y_t = \mu \mathbf{1} + \rho_0 W_t \Delta y_t + \overline{\rho} W_t y_{t-1} + \overline{\psi} y_{t-1} + X_t \beta + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma). \tag{2}$$

I estimate equation (2) separately for each quarter $t = 1, \ldots, T$ from purely cross-sectional information. The reason for this approach is possible time-variation in parameters. Given the market turbulence and various evidence for increasing market fragmentation in the period under investigation, time-variation in parameters may be important.

I follow the standard approach of estimating equation (2) by maximum likelihood (LeSage and Pace, 2009) in order to account for the endogeneity bias that arises due to the presence of $W_t y_t$ on the right-hand side of the equation. I also cross-check the results with Gibbs-sampler estimates using an uninformative prior as proposed by LeSage and Pace (2009:123ff). As to data transformations of the dependent variable, trading volumes $\left\{ z^L_{i,t}, z^B_{i,t}, z^V_{i,t} \right\}$ are taken in logs. As $z^N_{i,t}$ can take also attain negative values, I use the percentage to total trading volume, $z^N_{i,t} / z^V_{i,t}$ instead. For all variables, I demean the data prior to estimation. That is, the dependent variable is transformed to $y_{i,t} - T^{-1} \sum_{t=1}^{T} y_{it}$..[2]

Identifiability of parameter ρ_0 has gained some attention in the literature. As discussed e.g. by Bramoullé and Fortin (2009), the estimation of network dependence effects raises two main challenges. The first challenge is correlated effects, i.e. correlation between network formation and unobserved bank characteristics that affect interbank trading activity. In order to avoid

[2] I use Matlab codes provided by LeSage on http://www.spatial-econometrics.com/. Note that the presence of the lagged dependent variable, y_{t-1}, does not cause any difficulty, as I use purely cross-sectional data. Hence, the well-known issues with the consistency of estimates in spatial dynamic panel data models (see Elhorst, 2012) do not apply.

spurious estimates of ρ_0, Bramoullé and Fortin (2009) suggest including individual fixed effects and appropriate control variables in the equations. In the present application, the country location of a bank may give rise to correlated effects. In equation (2), individual bank fixed effects are therefore accounted for by demeaning the data prior to estimation, while time fixed effects are estimated from constant μ. I also include country-specific control variables X_t in the regressions, which are described in section 4.

The second challenge to identifiablity is the reflection problem studied by Manski (1993) and Moffitt (2001). Bramoullé et al. (2009) present conditions for identifiability in the case that control variables X_t are pre-determined to y_t and $\beta \neq 0$. In this case, a sufficient condition for identifiability in period t is that matrices I_n, G, G^2, and G^3, where $G = \text{sign}(W_t)$, are linearly independent. The intuition is that so-called *intransitive triplets* in business relations allow for forming local instruments: given links from i via j to k, but not from k to j, the partial correlation between i and j acts as an instrument for the influence of j on k. Given the complex structure of real-world financial networks, this condition is almost certainly fulfilled once the network is sufficiently sparse.

3 The Euro Area Money Market

The data set contains daily observations on unsecured bilateral overnight loans among 322 consolidated banking groups located in the euro area, ranging from June 2008 to March 2013. The source of the data is the euro area TARGET2 system, which is used to settle payments connected with monetary policy operations, interbank payments, and transactions related to other payment and securities settlement systems. The TARGET2 system is operated by the European system of Central Banks and is the principal payment settlement system within the euro area accounting for about 90% of interbank payments (ECB, 2013). As there are different types of payments that can be settled through TARGET2, interbank overnight loans need be identified from certain search criteria. Frutos et al. (2014) adapt the Furfine (1999) algorithm for this purpose. The algorithm identifies overnight interbank loans from the requirement that a payment flow is matched by a flow in the opposite direction on the following day (with certain limits on the implied interest rate), and uses further information on the transaction characteristics stored in TARGET 2. Frutos et al (2014) also validate the findings against data for the unsecured money market in Spain, which are reported in the MID post-trading structure and find a high accuracy of their results. I use a version of the data set from Garcia-de-Andoain et al. (2014), which has been further refined by consolidating individual banks into banking groups.

Table 1: Timeline of Events

Date		Description
Sep 15,	2008	Lehman bankruptcy
May 7,	2009	ECB introduces Covered Bonds Purchasing Program First ECB 1-year Long-Term Refinancing Operation (LTRO)
Sep 29,	2009	Greece's Prime Minister admits that Greek economy is in 'intensive care'
Dec 8,	2009	Third ECB 1-year Long-Term Refinancing Operation (LTRO)
Dec 15,	2009	FITCH downgrades Greece's credit rating
Apr 23,	2010	Greece seeks financial support
May 10,	2010	ECB introduces Security Markets Programme (SMP) Decision to set European Financial Stability Facility (EFSF)
Nov 21,	2010	Ireland seeks financial support
Apr 6,	2011	Portugal requests activation of aid mechanism
July 1,	2011	Interest rates on Italian and Spanish government bonds start to rise
Nov 16,	2011	Monti becomes Italy's new prime minister forming a technocrat government
Dec 8,	2011	ECB announces measures to support bank lending and money market activity
Dec 22,	2011	First ECB 3-year Long-Term Refinancing Operation (LTRO)
Mar 1,	2012	Second ECB 3-year Long-Term Refinancing Operation (LTRO)
Nov 20,	2012	General elections in Spain
Jun 27,	2012	Cyprus requests financial support
Jul 20,	2012	Eurogroup grants financial assistance to Spain's banking sector
Jul 26,	2012	'Whatever it takes ' speech by ECB president Draghi in London
Sep 6,	2012	ECB announces technical features of Outright Monetary Transaction Programme

Figure 1 shows the evolution of aggregate market activity, network density, and country averages of overnight interbank interest rates together with their dispersion. These statistics are subject

Fig 1a: Interbank market activity

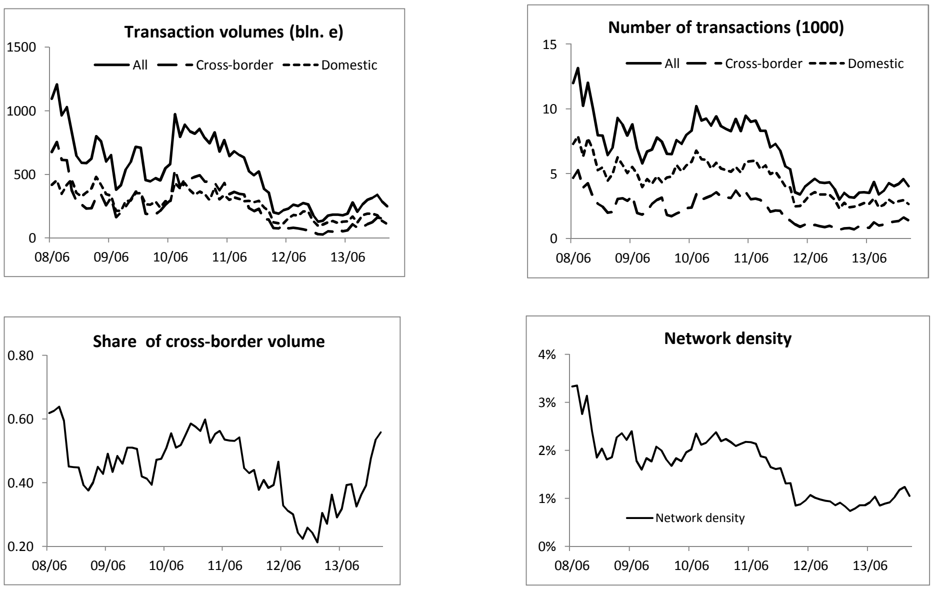
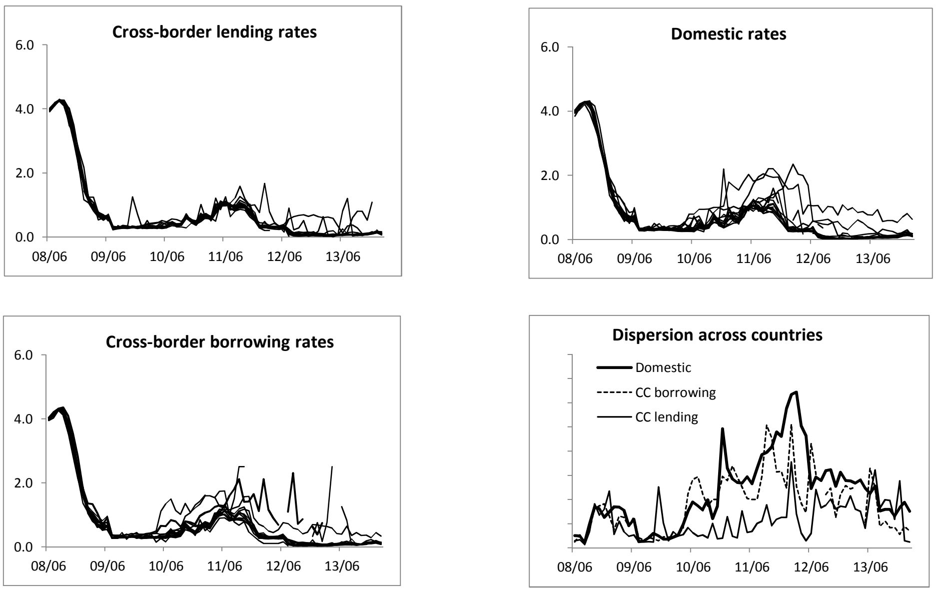


Fig 1b: Interbank market interest rates



to substantial shifts over time, which can be related to major crisis events and subsequent policy interventions, as summarised in Table 1 (Garcia-de-Andoain et al., 2015).[3]

The sample starts shortly before the Lehman event in September 2008. With the beginning of the financial crisis, transaction volumes dropped by about 50% until mid-2009, while the share of cross-border transactions fell from 60% to below 40%. At the same time, network density stayed at slightly above 1%, and cross-country dispersion in interest rates rose only moderately (Fig 1b). This indicates that the network remained integrated despite the stress on individual banks. After the various policy interventions of May 2010 aimed at calming down the Greek crisis - notably the creation of the EFSF and the ECB Securities Market Purchasing (SMP) program - total transaction volumes recovered rapidly close to pre-crisis levels.[4]

With the re-emergence of the sovereign debt crisis in mid-2011, market activity dropped for a second time. The decline in network density and the hike in interest rate dispersion indicates substantial fragmentation of the network during this period. In response to the crisis, the ECB launched 3-year long-term refinancing operations (LTROs) in December 2011 and March 2012 in order to support the market with ample liquidity. These interventions may have contributed to the continued decline in market volume until June 2012 due to some crowding out of interbank activity. However, at the same time, they appear to have supported the reintegration of the interbank network: its density stabilised in early 2012, while interest dispersion fell back to the levels of 2010. Thereafter, the market remained stable at a subdued level.

4 Results from Spatial Regressions

4.1 Data selection

One complication with the estimation of equation (2) is the sparseness of the network for a given period. While all banks in the data set undertake at least one transaction within the sample,

[3] Garcia-de-Andoain et al. (2015) provide a more extensive discussion of the timeline of events. See also http://www.ecb.europa.eu/ecb/html/crisis.en.html and http://www.britannica.com/EBchecked/topic/1795026.

[4] Network density is defined as the number of bilateral links within a period, divided by the number of all possible links, $n(n-1)/2$, where n is the number of nodes in the network. Interest rate dispersion refers to the standard deviations across the country averages of interest rates.

a high share of banks is inactive for any given period. This implies a sharp hike at zero in the distribution of trading volumes, which precludes using a linear model for the entire data set. At the same time, for obvious reasons, considering networks, which consist only of banks that are active in the very same period (and therefore consist of different sets of banks in each period) may result in selection bias when estimating equation (2).

I therefore focus on a subset of sufficiently active banks in the interbank network. I aggregate the data to *quarterly frequency* and keep only those banks that are active in *all but at most a certain number k of quarters*. In doing so, I maintain a sufficiently stable set of banks over the entire sample, while avoiding a hike at zero in the distribution of transaction volumes.

Table 2: Bank Location

Treshold k	All	6	4	3	0
EA	322	102	82	63	31
AT	24	10	10	9	3
BE	7	3	2	2	1
CY	5	1			
DE	59	13	12	10	3
ES	71	14	9	6	
FI	6	1	1	1	
FR	17	7	6	5	
GR	12	7	5	4	2
IE	6	3	1	1	
IT	67	31	29	21	8
LU	4	2	2	2	
NL	17	5	3	2	1
PT	16	3	1		
SI	8	1			
SK	3	1	1		

The table shows the number of active banks in individual countries for various values of activity threshold k. The first column (All) shows the overall number of banks per country, the remaining columns show the number of banks that are active in all but k quarters. EA refers to the euro area as a whole.

Tables 2 and 3 show the geographical distribution and various network statistics for different values of threshold k. The choice of of k turns out to have a moderate impact on the size of the network and its density. A value of $k = 2$ leaves 63 banks, while $k = 6$ gives 102 banks. By construction, network densities increase with smaller k. In the network of 102 banks in 2008 Q3 about 11% of all possible links are formed, while this number increases to 18% for the network of 63 banks.

The below estimates are based on a value of $k = 6$, i.e. the data set of 102 banks. Estimates are reasonably robust: using values of $k = 2$ and $k = 4$ does not change them in any important way. As shown in Table 2, for $k = 6$, banks are spread across 15 euro area member states. 31 of those banks are located in Italy, 14 in Spain and 13 in Germany, but, apart from a few small and peripheral ones, all euro area member states are represented with at least 2 banks. The 102 banks account for in between 43% and 67% of total transaction volume in the entire network. The high share reflects the core-periphery structure of interbank networks (Craig and von Peter, 2014), with a high share of activity taking place in a highly connected core. Garcia-de-Andoain et al. (2015) estimate the core of the euro area interbank network to contain about 50 banks. The data set of 102 banks may therefore be regarded as representing some extended core of the euro area interbank market.

The demeaned trading volumes and interest rates for the individual banks appear stationary. Persistence is moderate in all series with the first-order autocorrelation being generally below 0.8, while the presence of unit roots is generally rejected by Dickey-Fuller tests.

Table 3: Properties of Reduced Networks

	Network density				Share in total volume		
Treshold k	All	6	4	2	6	4	2
Nr of banks	322	102	82	63	102	82	63
2008-3	.03	.11	.14	.18	.43	.37	.31
2009-3	.03	.11	.14	.17	.63	.56	.52
2010-3	.03	.13	.16	.19	.64	.59	.53
2011-3	.02	.10	.13	.15	.61	.55	.47
2012-3	.01	.06	.08	.11	.64	.50	.43
2013-2	.01	.07	.09	.12	.67	.63	.55

The table shows network statistics for various values of activity treshold k. Column (All) refers to the overall number of banks, while the remaining columns show the number of banks that are active in all but at most k quarters.

4.2 Main Estimates

I turn to the estimates of equation (2) for trading volumes and interest rates as defined in section 2. To account for country-specific effects, I consider three control variables X_t: a GIPS dummy set equal to 1 for banks located in Greece, Ireland, Portugal, and Spain ($GIPS_t$); the 10-year government bond spreads of the bank home country vis-a-vis Germany (r_t^G); and the European Commission business sentiment indicator (BCI_t).

Preliminary estimates find $\overline{\rho}$ to be insignificant in almost all cases and I therefore impose $\overline{\rho} = 0$. By contrast, parameter $\overline{\psi}$ is generally significant and I therefore include the lagged dependent variable y_{t-1} in the equation. Estimates of control variables are insignificant for most periods, but they do turn significant in periods of market turbulences or of ECB interventions in many cases.

Estimates of spatial correlation coefficient ρ_0 are shown in Figure 2 and Table 4. Tables A.1 to A.6. provide the detailed estimation results. The findings may be summarised as follows:

- First, for net lending volumes and the lending-borrowing spread, estimates of ρ_0 are consistently negative, with only three minor exceptions. The average estimates across all periods amount to $-.22$ for volumes and $-.20$ for the spread, respectively. Estimates are substantially higher and significant during periods of market turmoil, notably the Lehman event (2008 Q4), the 2011 sovereign debt crisis and the 3-year LTROs launched by the ECB in December 2011 and March 2012 (see Table 1).
- Second, spatial correlations in total trading volumes are mostly positive. However, the average estimate is rather low at 0.14. Significant estimates appear at the onset of the Greek crisis (2009 Q4 and 2010 Q1) and in 2011 Q1.
- Third, estimates of spatial correlation in lending and borrowing volumes are mostly negative, but very small and never significant.
- Fourth, estimates for borrowing rates are of inconsistent sign. However, significant positive estimates are obtained precisely in periods of major ECB policy interventions, such as the

Covered Bonds programme, the first set of LTROs (2009 Q2 and Q3), the Securities Market Purchasing Programme (2010 Q2), and the 3-year LTROs in 2011 Q4 (see Table 1). The exception to this rule is a significantly negative estimate in 2012 Q1. No clear pattern emerges for lending rates.

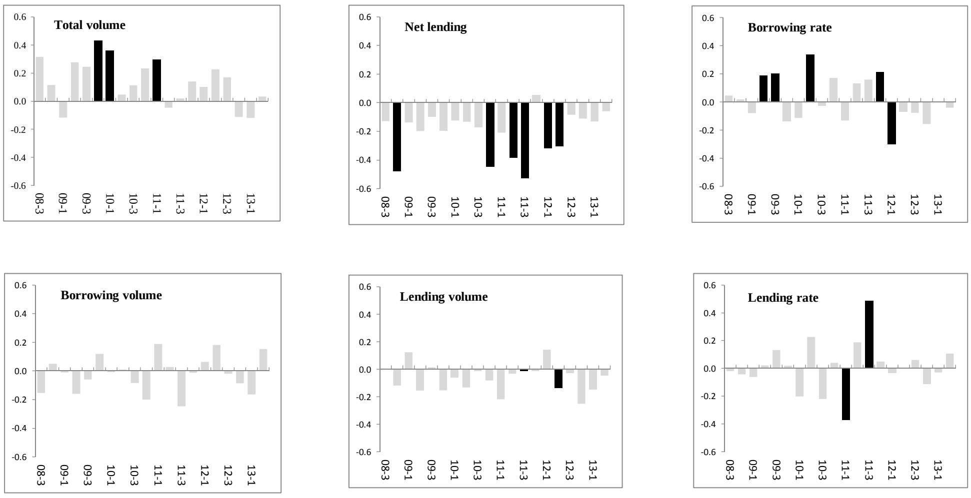
Table 4: Estimates of Spatial Correlation Coefficients

	Total volume	Net lending	Lending volume	Borrowing volume	Lending rate	Borrowing rate	Rate spread
2008-3	*.31	-.13	.00	-.15	-.02	.05	-.10
2008-4	.11	**-.48	-.12	.05	-.04	.02	*-.31
2009-1	-.12	-.14	.12	-.01	-.06	-.08	-.18
2009-2	.28	-.20	-.16	-.16	.02	**.19	-.22
2009-3	.25	-.10	.01	-.06	.13	**.20	.01
2009-4	**.43	-.20	-.15	.12	.02	-.14	-.17
2010-1	**.36	-.12	-.06	-.01	*-.20	-.11	-.22
2010-2	.05	-.13	-.13	.01	.23	**.34	-.08
2010-3	.11	-.17	-.02	-.09	-.22	-.03	-.23
2010-4	.23	**-.45	-.08	-.20	.04	.17	-.22
2011-1	**.30	-.21	-.22	.19	**-.37	-.13	*-.30
2011-2	-.05	*-.39	-.03	.03	.19	.13	-.18
2011-3	.02	*-.53	-.01	-.25	**.49	.16	**-.65
2011-4	.14	.05	-.01	-.01	.05	**.21	.04
2012-1	.10	**-.32	.14	.06	-.03	**-.30	*-.27
2012-2	.23	**-.31	-.14	.18	.00	-.07	**-.38
2012-3	.17	-.08	-.03	-.02	.06	-.08	-.13
2012-4	-.11	-.11	-.35	-.09	-.11	-.16	-.11
2013-1	-.12	-.13	-.15	-.17	-.03	.00	-.13
2013-2	.03	-.06	-.05	.15	.11	-.04	-.11

The table shows estimates of coefficient ρ_0 in equation (2). * and ** indicate significance at the 10% and5% levels, respectively.

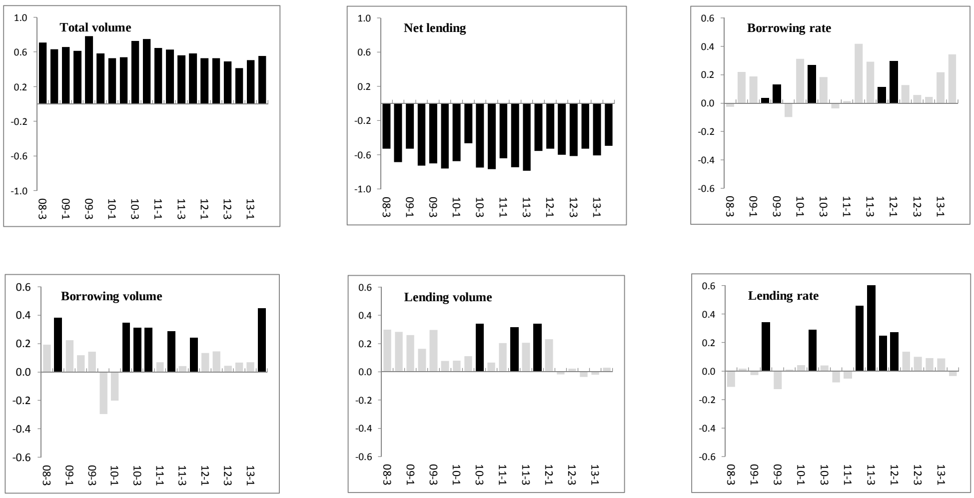
The above findings stand in sharp contrast to those of Cohen-Cole et al. (2011). The latter paper reports significant positive estimates of ρ_0 of around 0.6 for lending volumes and even somewhat higher values for lending rates. The study differs in various respects from the present approach. Starting from transaction level data of the Italian e-mid, Cohen-Cole et al (2011) construct a

Figure 2: Main Estimates of Spatial Correlation Coefficients



The figure shows estimates of coefficient ρ_0 from equation (2). Black bars indicate significance at the 5% level. See also Table 4.

Figure 3: Estimates of Spatial Correlation Coefficients from Cohen-Cole equation



The figure shows estimates of coefficient ρ_0 from restricted equation (1) under the specification of Cohen-Cole et al. (2011), which excludes bank fixed effects and the lagged dependent variable ($\psi_1 = \rho_1 = 0$). Black bars indicate significance at the 5% level.

sequence of networks from blocks of 1000 consecutive trades within a day and obtain estimates of ρ from each of these networks. Hence, they consider only actively trading banks and define neighbouring relations in a circular way from the actual trades on the very same data set. The neglect of non-active banks might not only give rise to selection bias: as weighting matrix W_t is constructed from the same set of trades that is used to construct the dependent variable, i.e. $w_{ij,t} = z_{ij,t} / z^L_{i,t}$, it is not predetermined, as required. This gives rise to circularity in the definition of neighbours, the consequences of which are not immediately obvious.[5] Finally, and perhaps most important, Cohen-Cole et al. (2011) use a basic version of equation (1) with $\psi = \rho_1 = 0$. Data are *not* mean-adjusted and hence, Cohen-Cole et al. (2011) ignore bank fixed effects.

Part of the difference in the findings may be due to the different periodicity of the data. However, when applying the Cohen-Cole et al. (2011) specification to my data set, I find results that are similar to theirs. The corresponding estimates of ρ_0 are shown in Figure 3. Spatial correlations in lending and borrowing volumes turn positive, although estimates are not always significant, while estimates for total and net lending volumes are very large and always significant. However, this appears to merely reflect a positive correlation between the level of overall transaction volumes among neighbours. Adding either y_{t-1} or bank fixed effects results in estimates close to those reported in Table 4. Hence, the explanation for the differences lies pre-dominantly in a misspecification of the approach of Cohen-Cole et al. (2011).

4.3 Discussion

To summarise, the above estimates find predominantly positive network dependence in total volumes, and negative dependence in net lending volumes and the lending-borrowing interest rate spread. Significant effects arise only in periods of market turmoil or major policy interventions such as the sovereign debt crisis in 2011 and the first half of 2012 when the ECB launched its long-term refinancing operations. Estimates of network dependence in lending and borrowing volumes are very small and insignificant for all periods under consideration. For borrowing rates, estimates are of inconsistent sign, but significantly positive estimates emerge in periods of major

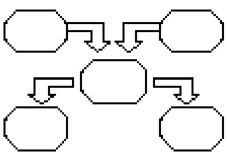
[5] It can be shown that the circular definition of W gives rise to a bias in estimates of ρ, which may become substantial in case of low network density.

ECB interventions (see Table 1).

The estimates therefore provide little support for the view that network dependence plays a major role in the propagation or even amplification of shocks in the interbank market. In fact, the negative estimates for net lending volumes and the lending-borrowing spread suggest that network relationships mitigate rather than amplify shocks to the liquidity position of individual banks. In this sense, neighbours do occasionally matter: they act to dampen shocks to a bank's liquidity needs by partly counterbalancing their own net lending.

Bräuning et al. (2015) present a dynamic model of the interbank market that gives rise to such mechanism: assume, that bank i faces excess liquidity due to an idiosyncratic shock and aims at raising its net lending. Interest rates on interbank loans are largely determined by the lender. Under these conditions, bank i would reduce its borrowing at a fixed rate and, at the same time, aim at increasing its lending by offering lower interest rates to potential borrowers. That is, it would accept a lower lending-borrowing interest rate spread.

Figure 4: Implications of an Idiosyncratic Liquidity Shock



	Net lending	Total Volume	Spread
Lenders	↓	↓	0
Bank i	↑	↓	↓
Borrowers	↓	↑	↑

Part of these desired shifts would be absorbed by offsetting adjustments of the neighbours of bank i. Lenders to bank i would find their overall lending reduced, while potential borrowers may take advantage of lower rates and increase their borrowing. As a result, the net lending of both lenders and borrowers would decline, and the lending-borrowing spread of borrowers would increase. Hence, this mechanism introduces negative spatial correlation between bank i and its neighbours in these two variables. The effect on total volumes is ambiguous (Fig. 4).

In a second round, the neighbours of bank i would then adjust their own liquidity positions. For instance, its borrowers might find it profitable to increase their lending by passing on the lower interest rates. The significantly positive estimates for borrowing rates after ECB policy interventions indeed indicate that network relationships may have played a role in channeling the ample liquidity provided by the ECB to the market with lower rates gradually being passed on.[6]

I conclude the discussion with two remarks on econometric issues, related to correlated effects and the selection of banks in the spatial regressions. As noted in section 2, a correlation between link formation and unobserved variables that affect the dependent variable y_t could give rise to spurious non-zero estimates of ρ_0. While the regressions include country-specific control variables, it can not be excluded that, beyond country-specific effects, interbank business relations are correlated with bank's business models or other features that affect interbank trading behaviour. However, two features of the estimation design used in this paper should act to limit the impact of correlated effects. First, I account both for bank and time fixed effects in the estimates. Second, as $\overline{\rho}$ was found to be insignificant, spatial correlation enters equation (2) only terms of quarterly *changes*, i.e. coefficient ρ_0. Given that bank characteristics, in general, change only gradually over time, it is unlikely that the determinants of past business relations are correlated with current changes in interbank market activity. Third, as to the results for net lending and the lending-borrowing spread, it is difficult to see how unobserved bank characteristics could result in spurious negative estimates of ρ_0.

As to the selection of banks, I chose to limit the analysis to sufficiently active banks. Large banks in the core of the interbank network are therefore overrepresented in the sample. Garcia-de-Andoain et al. (2015) present some evidence that smaller, peripheral banks were more affected by market disruptions than the core, as they suffered sharper declines in borrowing volumes in these episodes. Hence, they may be subject to higher network dependence than core banks.

[6] Second-round effects take also place on the lender's side, of course (see Bräuning et al., 2015).

5 Conclusions

Network dependence in interbank networks relates to the hypothesis that the behaviour of a bank is affected by the behaviour of its neighbours in the network. To the extent at which these effects are at work, the network would matter for the allocation of liquidity and interest rates. The present study employed linear spatial regressions to explore the size of these effects in the euro area interbank market during the financial crisis. Estimates are based on a sequence of 20 quarterly networks in between 2008 Q3 and 2013 Q2 of a stable set of 102 banks that are sufficiently active over the entire sample.

I find predominantly negative network dependence in net lending volumes and the lending-borrowing spread, and positive effects in total volumes and borrowing rates.

Generally, the scale of network dependence is rather small. Significant effects arise only in periods of market turmoil or major policy interventions such as the sovereign debt crisis in 2011 and the first half of 2012 when the ECB launched its long-term refinancing operations. The estimates do therefore not support the view that network dependence would have played an important role in the propagation or even amplification of shocks in the interbank market. In fact, the predominantly negative estimates for net lending volumes and the lending-borrowing spread suggest that network relationships mitigate rather than amplify idiosyncratic shocks to the liquidity position of individual banks, as neighbours would act to partly absorb these shocks by counterbalancing their own net lending position. It may be of interest to confront these findings with simulation results from interbank network simulation models (e.g. Co-pierre, 2011; Bräuning et al., 2015).

These findings are in contrast to Cohen-Cole et al. (2011), who report strongly positive network dependence in both lending volumes and rates. While the two studies differ in many methodological aspects, I present evidence for misspecification of the Cohen-Cole et al. (2011) approach.

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Table A.1: Estimates of Equation (2) for Total Volume

			Coefficient estimates						t-values					
	nobs	R^2	μ	ψ	r^G	BCI	GIPS	ρ_0	μ	ψ	r^G	BCI	GIPS	ρ_0
2008-3	90	0.21	0.630	0.514	-0.025	0.026	0.441	0.325	0.62	4.40	-0.10	0.99	1.58	1.83
2008-4	91	0.30	0.342	0.605	0.018	0.011	-0.437	0.112	0.35	6.19	0.11	0.43	-1.89	0.64
2009-1	94	0.26	1.161	0.410	-0.075	0.018	-0.145	-0.111	1.29	5.98	-0.28	0.69	-0.72	-0.69
2009-2	91	0.04	-0.624	0.217	0.109	-0.025	0.009	0.281	-0.92	2.30	0.42	-0.98	0.05	1.59
2009-3	91	0.10	0.095	0.198	0.025	-0.019	-0.085	0.248	0.33	2.98	0.24	-1.04	-0.43	1.55
2009-4	88	0.12	-0.348	0.245	0.152	-0.045	-0.607	0.422	-0.95	1.68	0.95	-1.00	-1.76	2.65
2010-1	90	0.39	0.102	0.453	0.005	-0.001	0.063	0.348	0.87	6.79	0.07	-0.04	0.30	2.41
2010-2	86	-0.02	0.947	0.022	0.000	0.007	-0.061	0.047	4.83	0.29	0.01	0.49	-0.33	0.25
2010-3	92	0.26	0.335	0.441	0.001	0.002	0.190	0.107	1.63	5.99	0.02	0.13	0.99	0.62
2010-4	92	0.03	0.534	0.260	-0.046	-0.024	-0.272	0.244	2.70	2.73	-1.24	-1.71	-1.15	1.44
2011-1	94	0.36	-0.022	0.578	0.002	-0.003	-0.026	0.291	-0.13	7.53	0.07	-0.20	-0.14	2.10
2011-2	92	0.25	0.352	0.448	-0.042	-0.036	-0.124	-0.048	1.72	4.57	-2.11	-2.03	-0.57	-0.26
2011-3	94	0.50	-0.005	0.614	-0.033	-0.018	-0.085	0.016	-0.03	8.45	-3.21	-1.07	-0.36	0.10
2011-4	92	0.34	-0.453	0.340	-0.043	-0.035	0.794	0.137	-2.21	3.09	-3.19	-1.47	2.60	0.89
2012-1	87	0.36	-0.091	0.570	-0.010	0.005	-0.092	0.103	-0.25	5.58	-0.33	0.18	-0.35	0.68
2012-2	89	0.49	-1.888	0.623	-0.113	-0.125	0.256	0.226	-2.89	6.42	-2.88	-2.88	0.80	1.89
2012-3	89	0.38	-0.615	0.505	0.032	-0.030	-0.208	0.175	-0.75	5.91	0.60	-0.53	-0.69	1.33
2012-4	88	0.55	-0.495	0.822	0.047	-0.032	-0.572	-0.110	-1.11	9.71	1.13	-0.94	-2.11	-0.94
2013-1	90	0.55	-0.711	0.510	-0.053	-0.077	-0.278	-0.126	-1.91	8.67	-1.29	-2.64	-1.24	-1.12
2013-2	89	0.44	0.077	0.571	-0.080	-0.019	-0.571	0.029	0.28	6.06	-1.34	-0.55	-1.85	0.21

The table shows estimates of equation (2). Estimates are conducted separately for each quarter as indicated in the left column. Nobs and R2 refer to the number of observations and the explained variance, respectively. rG, BCI, and GIPS refer to the government bond spreads to Germany, the Business Confidence Indicator and the GIPS dummy, respectively.

Table A.2: Estimates of Equation (2) for Net Lending

			Coefficient estimates						t-values					
	nobs	R^2	μ	ψ	r^G	BCI	GIPS	ρ_0	μ	ψ	r^G	BCI	GIPS	ρ_0
2008-3	90	0.13	-1.239	0.347	0.272	-0.040	-0.605	-0.128	-1.70	3.10	1.48	-1.98	-2.72	-0.63
2008-4	91	0.19	-0.110	0.392	0.076	-0.002	0.133	-0.475	-0.17	4.36	0.70	-0.14	0.88	-2.78
2009-1	94	0.19	0.021	0.365	0.234	0.003	-0.314	-0.138	0.03	4.22	1.07	0.14	-1.89	-0.84
2009-2	93	0.22	-0.039	0.507	0.092	0.003	0.066	-0.202	-0.06	4.87	0.37	0.11	0.35	-1.15
2009-3	93	0.35	0.175	0.540	0.243	0.013	-0.132	-0.100	0.56	6.09	2.06	0.65	-0.61	-0.64
2009-4	91	0.14	-0.174	0.430	-0.160	-0.019	0.034	-0.194	-0.52	3.99	-1.12	-0.46	0.11	-1.04
2010-1	90	0.41	-0.266	0.478	-0.015	-0.039	-0.736	-0.123	-3.36	6.47	-0.31	-2.63	-4.18	-0.84
2010-2	91	0.24	-0.135	0.435	-0.019	-0.009	0.453	-0.129	-1.78	4.60	-0.39	-0.54	1.97	-0.76
2010-3	93	0.24	-0.129	0.420	0.067	0.003	-0.335	-0.172	-1.10	4.74	1.45	0.22	-1.73	-1.04
2010-4	94	0.06	-0.215	0.231	0.034	0.003	0.162	-0.442	-1.84	2.36	0.93	0.20	0.67	-2.51
2011-1	94	0.28	0.101	0.510	0.013	-0.001	-0.211	-0.210	1.45	5.77	0.46	-0.05	-1.21	-1.33
2011-2	94	0.27	0.076	0.512	0.026	0.002	-0.334	-0.392	0.66	5.37	1.54	0.10	-1.68	-2.47
2011-3	94	0.09	0.250	0.256	0.000	0.021	0.183	-0.528	1.87	2.82	-0.04	1.31	0.83	-3.32
2011-4	92	0.16	-0.123	0.425	-0.012	-0.005	0.276	0.052	-0.82	4.17	-1.69	-0.31	1.30	0.32
2012-1	88	0.16	0.167	0.465	0.032	0.015	0.023	-0.312	0.60	4.62	1.81	0.68	0.11	-2.09
2012-2	89	0.50	0.954	0.595	0.016	0.063	0.208	-0.303	3.16	7.80	0.97	3.13	1.37	-2.37
2012-3	89	0.63	0.069	0.824	-0.011	-0.002	-0.100	-0.084	0.19	10.31	-0.46	-0.06	-0.67	-0.77
2012-4	88	0.46	-0.463	0.702	-0.013	-0.035	0.099	-0.109	-1.71	7.87	-0.49	-1.67	0.56	-0.86
2013-1	90	0.41	-0.095	0.556	-0.010	-0.004	-0.039	-0.138	-0.37	7.08	-0.31	-0.19	-0.22	-1.10
2013-2	89	0.28	0.073	0.549	0.010	0.002	-0.096	-0.063	0.40	6.06	0.25	0.08	-0.48	-0.44

See Table A.1 for explanations.

Table A.3: Estimates of Equation (2) for Lending Volume

			Coefficient estimates						t-values					
	nobs	**R^2**	μ	ψ	r^G	BCI	GIPS	ρ^D	μ	ψ	r^G	BCI	GIPS	ρ^D
2008-3	87	0.21	-0.844	0.589	0.302	-0.011	-0.173	0.004	-0.53	5.13	0.72	-0.24	-0.34	0.02
2008-4	86	0.26	-1.994	0.528	0.279	-0.036	-0.440	-0.116	-1.52	5.85	1.31	-1.10	-1.48	-0.71
2009-1	89	0.30	0.899	0.484	0.003	0.024	-0.278	0.122	0.77	6.42	0.01	0.71	-1.02	0.86
2009-2	87	0.09	-2.475	0.424	0.877	-0.052	-0.443	-0.160	-1.73	3.14	1.59	-0.98	-1.06	-0.90
2009-3	87	0.36	0.618	0.477	0.350	0.039	-0.167	0.012	1.11	6.46	1.73	1.12	-0.45	0.08
2009-4	82	0.11	-1.075	0.360	0.073	-0.068	-0.915	-0.156	-1.78	3.01	0.29	-0.95	-1.66	-0.90
2010-1	79	0.33	-0.620	0.410	0.034	-0.065	-1.128	-0.059	-3.48	4.87	0.36	-2.37	-3.30	-0.36
2010-2	83	0.15	0.121	0.444	-0.171	-0.022	0.439	-0.126	0.73	4.23	-1.70	-0.67	0.94	-0.75
2010-3	89	0.33	-0.221	0.436	0.144	0.007	-0.675	-0.015	-1.01	6.28	1.71	0.28	-1.95	-0.10
2010-4	92	0.14	0.016	0.384	-0.111	-0.038	0.044	-0.082	0.07	4.45	-1.57	-1.41	0.09	-0.47
2011-1	92	0.21	0.056	0.462	-0.012	-0.004	-0.426	-0.215	0.41	5.27	-0.23	-0.18	-1.20	-1.27
2011-2	89	0.33	-0.087	0.537	0.002	-0.023	-0.652	-0.036	-0.45	6.59	0.08	-0.84	-1.82	-0.22
2011-3	90	0.37	-0.166	0.476	-0.061	-0.016	0.015	-0.012	-0.74	5.87	-3.98	-0.59	0.04	-0.07
2011-4	86	0.32	-1.179	0.144	-0.076	-0.053	1.014	-0.015	-3.86	1.43	-4.62	-1.78	2.58	-0.09
2012-1	81	0.35	-0.177	0.587	-0.016	0.015	0.369	0.151	-0.32	5.62	-0.44	0.37	0.99	1.15
2012-2	81	0.56	-1.576	0.686	-0.107	-0.084	0.098	-0.136	-2.32	8.82	-2.93	-2.02	0.31	-1.13
2012-3	81	0.47	-0.384	0.820	0.092	0.005	-0.728	-0.025	-0.37	8.10	1.34	0.07	-1.80	-0.22
2012-4	76	0.46	-1.514	0.775	-0.028	-0.074	-0.274	-0.264	-2.22	7.62	-0.42	-1.51	-0.59	-1.95
2013-1	75	0.55	-2.077	0.509	-0.087	-0.144	-0.611	-0.154	-3.45	6.99	-1.37	-3.37	-1.51	-1.20
2013-2	83	0.61	-0.046	0.781	-0.078	-0.007	-0.694	-0.046	-0.12	9.78	-1.04	-0.17	-1.89	-0.40

See Table A.1 for explanations.

Table A.4: Estimates of Equation (2) for Lending Rate

			Coefficient estimates						t-values					
	nobs	**R^2**	μ	ψ	r^G	BCI	GIPS	ρ^D	μ	ψ	r^G	BCI	GIPS	ρ^D
2008-3	87	0.00	0.739	0.453	0.016	-0.004	0.044	-0.022	0.68	1.77	0.16	-0.35	0.35	-0.11
2008-4	82	0.07	0.464	-0.180	0.024	-0.008	-0.021	-0.043	1.69	-2.94	0.62	-1.34	-0.37	-0.24
2009-1	86	0.00	-0.083	-0.068	-0.081	0.003	0.014	-0.064	-0.46	-1.25	-1.49	0.64	0.32	-0.39
2009-2	79	0.33	-0.317	0.159	-0.105	0.008	0.013	0.020	-2.88	3.32	-3.37	2.72	0.60	0.12
2009-3	79	0.30	-0.339	0.318	-0.043	-0.001	0.016	0.140	-2.77	4.11	-2.37	-0.33	0.50	0.88
2009-4	82	0.16	-0.334	0.423	0.011	0.003	0.004	0.019	-2.54	3.85	0.46	0.38	0.07	0.11
2010-1	75	0.36	-0.322	0.630	-0.006	-0.001	0.064	-0.200	-3.80	6.77	-0.65	-0.27	1.94	-1.91
2010-2	76	0.20	-0.240	0.206	-0.002	-0.002	-0.094	0.224	-2.60	2.35	-0.25	-0.89	-2.76	1.39
2010-3	83	0.21	-0.283	0.331	-0.015	0.001	0.084	-0.223	-3.66	3.88	-1.65	0.32	2.11	-1.25
2010-4	91	0.15	-0.166	0.367	0.007	0.004	-0.029	0.040	-2.65	4.04	0.64	1.09	-0.42	0.24
2011-1	91	0.19	0.229	0.365	0.018	0.005	0.010	-0.376	6.79	4.53	2.32	1.51	0.19	-2.19
2011-2	82	0.25	-0.026	0.582	-0.006	-0.010	-0.056	0.180	-0.73	5.08	-1.29	-2.78	-1.23	1.03
2011-3	91	0.43	-0.195	0.392	-0.006	-0.028	-0.298	0.474	-3.23	2.93	-1.35	-3.43	-2.77	3.62
2011-4	76	-0.01	-0.592	-0.036	-0.004	-0.004	-0.019	0.053	-5.25	-0.89	-1.89	-1.07	-0.55	0.29
2012-1	69	0.27	-0.618	0.116	-0.012	-0.006	0.007	-0.034	-9.65	2.55	-5.24	-2.84	0.34	-0.46
2012-2	74	0.12	-0.675	0.231	-0.006	-0.001	0.057	-0.002	-4.63	3.47	-1.53	-0.25	1.67	-0.01
2012-3	71	0.10	-0.757	0.086	-0.011	-0.003	0.096	0.060	-7.16	1.15	-2.07	-0.56	2.88	0.73
2012-4	77	0.20	-0.637	0.322	-0.010	0.004	0.067	-0.110	-4.13	4.00	-2.03	1.14	2.08	-0.74
2013-1	72	0.60	-0.374	0.592	-0.010	-0.003	0.025	-0.030	-5.73	9.40	-2.81	-1.60	1.11	-0.86
2013-2	75	0.39	-0.389	0.426	0.000	-0.001	-0.026	0.102	-2.99	7.26	0.00	-0.34	-1.28	0.76

See Table A.1 for explanations.

Table A.5: Estimates of Equation (2) for Borrowing Volume

			Coefficient estimates						t-values					
	nobs	R^2	μ	ψ	r^G	BCI	GIPS	ρ_0	μ	ψ	r^G	BCI	GIPS	ρ_0
2008-3	81	0.2628	1.782	0.337	-0.044	0.073	1.154	-0.156	1.47	4.13	-0.14	2.15	2.95	-0.98
2008-4	79	0.1713	-0.364	0.478	-0.020	-0.002	-0.294	0.052	-0.28	4.42	-0.09	-0.07	-0.90	0.33
2009-1	83	0.1588	0.820	0.403	-0.552	0.021	0.160	-0.009	0.57	4.41	-1.26	0.52	0.48	-0.06
2009-2	84	0.285	-3.221	0.643	1.177	-0.083	-0.816	-0.159	-2.60	6.06	2.33	-1.82	-2.25	-1.09
2009-3	85	0.221	-0.119	0.544	-0.107	0.002	0.343	-0.060	-0.15	5.32	-0.34	0.03	0.66	-0.48
2009-4	80	0.4018	0.295	0.589	0.932	0.076	-0.932	0.120	0.45	6.54	3.48	1.02	-1.57	0.95
2010-1	80	0.5695	0.085	0.661	0.001	0.021	0.696	-0.007	0.53	10.06	0.01	0.84	2.28	-0.07
2010-2	86	0.3625	0.517	0.568	-0.125	0.018	-0.359	0.008	3.78	5.46	-1.34	0.59	-0.89	0.05
2010-3	87	0.455	0.246	0.558	-0.154	-0.016	0.433	-0.086	1.41	7.91	-2.20	-0.72	1.44	-0.58
2010-4	86	0.0971	0.316	0.273	-0.073	-0.030	-0.725	-0.196	1.72	2.66	-1.14	-1.29	-1.81	-1.10
2011-1	87	0.1721	-0.237	0.368	0.015	-0.008	0.169	0.188	-1.94	4.58	0.29	-0.38	0.53	1.26
2011-2	84	0.418	-0.154	0.826	-0.013	-0.011	-0.113	0.028	-0.63	7.54	-0.32	-0.32	-0.27	0.21
2011-3	77	0.2122	-0.361	0.471	-0.012	-0.023	-0.796	-0.248	-1.51	4.64	-0.64	-0.77	-1.89	-1.48
2011-4	81	0.3311	-0.765	0.671	-0.027	-0.014	0.512	-0.013	-2.43	5.87	-1.59	-0.42	1.19	-0.09
2012-1	78	0.3392	-0.732	0.579	-0.057	-0.018	0.103	0.067	-1.08	5.32	-1.15	-0.36	0.22	0.48
2012-2	74	0.4865	-2.061	0.607	-0.058	-0.123	-0.182	0.184	-2.17	6.50	-1.16	-2.12	-0.42	1.54
2012-3	73	0.3899	-1.133	0.647	0.141	-0.017	-0.836	-0.020	-0.89	6.48	1.89	-0.21	-1.84	-0.16
2012-4	71	0.5225	-0.028	0.689	0.046	0.024	-1.088	-0.087	-0.04	8.44	0.84	0.54	-2.61	-0.74
2013-1	75	0.3434	-1.422	0.527	-0.114	-0.091	0.328	-0.160	-2.24	6.23	-1.66	-2.04	0.75	-1.22
2013-2	77	0.3448	-0.057	0.639	-0.087	-0.001	0.051	0.154	-0.14	6.55	-1.05	-0.01	0.13	1.19

See Table A.1 for explanations.

Table A.6:Estimates of Equation (2) for Borrowing Rate

			Coefficient estimates						t-values					
	nobs	R^2	μ	ψ	r^G	BCI	GIPS	ρ_0	μ	ψ	r^G	BCI	GIPS	ρ_0
2008-3	79	0.06	0.291	-0.113	-0.042	-0.009	-0.073	0.018	0.85	-1.69	-0.84	-1.21	-1.05	0.10
2008-4	79	0.06	0.291	-0.113	-0.042	-0.009	-0.073	0.018	0.85	-1.69	-0.84	-1.21	-1.05	0.10
2009-1	80	-0.01	-0.241	0.060	-0.025	0.001	0.060	-0.081	-1.25	0.99	-0.43	0.22	1.34	-0.47
2009-2	83	0.39	0.039	0.290	-0.179	0.016	0.039	0.185	0.35	4.77	-4.26	4.01	1.25	2.07
2009-3	89	0.59	-0.039	0.723	-0.035	0.000	0.010	0.200	-0.50	9.90	-1.43	0.06	0.24	2.38
2009-4	86	0.49	-0.236	0.680	0.039	0.008	0.017	-0.132	-2.22	8.76	1.67	1.21	0.36	-0.93
2010-1	67	0.22	-0.499	0.272	-0.005	0.000	0.056	-0.113	-4.75	4.31	-0.87	-0.02	2.44	-0.69
2010-2	86	0.36	0.054	0.567	0.003	0.001	-0.078	0.342	0.75	7.03	0.27	0.42	-1.70	2.52
2010-3	74	0.23	-0.086	0.482	-0.011	-0.003	0.024	-0.027	-1.19	5.12	-1.01	-0.89	0.58	-0.15
2010-4	87	0.12	-0.076	0.367	0.006	0.002	-0.002	0.172	-1.65	3.75	0.52	0.54	-0.02	1.09
2011-1	82	0.01	0.177	0.165	0.009	-0.001	-0.059	-0.131	5.68	1.93	1.17	-0.35	-1.30	-0.78
2011-2	80	0.27	0.032	0.232	0.009	-0.005	0.036	0.130	0.79	2.07	1.74	-1.09	0.61	0.82
2011-3	81	0.39	-0.303	1.000	0.014	-0.019	-0.310	0.153	-3.33	3.71	1.82	-1.69	-1.95	1.08
2011-4	69	0.17	-0.445	0.083	0.000	0.004	0.046	0.212	-7.08	2.90	0.26	1.54	1.39	2.10
2012-1	80	0.21	-0.601	0.486	-0.009	-0.010	0.063	-0.312	-5.73	6.58	-1.52	-1.84	1.16	-2.73
2012-2	70	0.19	-0.807	0.295	-0.014	-0.011	0.001	-0.069	-5.51	3.94	-3.47	-2.52	0.02	-0.46
2012-3	72	0.45	-0.667	0.344	-0.012	-0.004	0.125	-0.079	-5.36	6.11	-2.43	-0.85	3.66	-0.93
2012-4	70	0.56	-0.600	0.435	0.008	0.003	0.071	-0.156	-6.67	7.15	2.01	1.14	2.20	-2.08
2013-1	72	0.31	-0.397	0.564	-0.005	-0.006	0.004	0.004	-3.40	5.36	-0.92	-1.60	0.10	0.04
2013-2	75	0.25	-0.504	0.414	0.005	-0.001	-0.071	-0.039	-4.41	5.10	0.76	-0.17	-2.41	-0.44

See Table A.1 for explanations.

Macroprudential Research Network

This paper presents research conducted within the Macroprudential Research Network (MaRs). The network is composed of economists from the European System of Central Banks (ESCB), i.e. the national central banks of the 27 European Union (EU) Member States and the European Central Bank. The objective of MaRs is to develop core conceptual frameworks, models and/or tools supporting macro-prudential supervision in the EU.

The research is carried out in three work streams: 1) Macro-financial models linking financial stability and the performance of the economy; 2) Early warning systems and systemic risk indicators; 3) Assessing contagion risks.

MaRs is chaired by Philipp Hartmann (ECB). Paolo Angelini (Banca d'Italia), Laurent Clerc (Banque de France), Carsten Detken (ECB), Simone Manganelli (ECB) and Katerina Šmídková (Czech National Bank) are workstream coordinators. Javier Suarez (Center for Monetary and Financial Studies) and Hans Degryse (Katholieke Universiteit Leuven and Tilburg University) act as external consultants. Fiorella De Fiore (ECB) and Kalin Nikolov (ECB) share responsibility for the MaRs Secretariat.

The refereeing process of this paper has been coordinated by a team composed of Gerhard Rünstler, Kalin Nikolov and Bernd Schwaab (all ECB).

The paper is released in order to make the research of MaRs generally available, in preliminary form, to encourage comments and suggestions prior to final publication. The views expressed in the paper are the ones of the author(s) and do not necessarily reflect those of the ECB or of the ESCB.

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